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Towards Living Machines: current and future trends of tactile sensing, grasping, and social robotics

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Abstract

The development of future technologies can be highly influenced by our deeper understanding of the principles that underlie living organisms. The Living Machines conference aims at presenting (among others) the interdisciplinary work of behaving systems based on such principles. Celebrating the 10 years of the conference, we present the progress and future challenges of some of the key themes presented in the robotics workshop of the Living Machines conference. More specifically, in this perspective paper, we focus on the advances in the field of biomimetics and robotics for the creation of artificial systems that can robustly interact with their environment, ranging from tactile sensing, grasping, and manipulation to the creation of psychologically plausible agents.

1. Introduction

In the last decade, robotics has successfully merged knowledge from automation, computer vision, artificial intelligence, and mechatronics, as well as human sciences (e.g. neuroscience, psychology, and philosophy), to achieve autonomous and intelligent systems that robustly interact with the environment. Despite the incredible progress in robotics, artificial intelligence, and other relevant fields, we are still not able to build artificial systems that can be compared to the dexterity and adaptability of living organisms. The development of future technologies can be highly influenced by our deeper understanding of the principles that underlie living systems.

This influence has also been evident in science fiction. An example is Westworld, a TV series that presents a futurist theme park with autonomous robots engineered to interact with humans. However, these robots have not achieved all human capabilities, as for example, their hands have not yet been perfected. Such examples highlight the importance of designing robust, dexterous, and reliable hands for grasping and manipulation actions. Indeed, reproducing the capabilities of the human tactile sense in machines is an important step in enabling robotic hands to reach the dexterity of the human hand, as it will have a profound impact on human society as machines become commonplace for physical labor [1]. Additionally, for robots to successfully interact with humans, they need to be perceived by a human interlocutor as physically and psychologically plausible. In this case, biomimetics represents the continuous advancement of the 'body' and the 'mind' of the robot to reproduce human-like capabilities.

Advances in the aforementioned areas have been presented in detail at the international conference of 'Living Machines' over the years. The aim of the conference is to present the development of artificial systems from interdisciplinary fields that are comparable to the functionalities, principles, and behaviors of living organisms (hence the name Living Machines). Indeed, there is a plethora of research domains that have been presented over the years within the context of the conference, and a first attempt to summarize the various clusters of research has been presented in [2]. Celebrating the 10th anniversary of the conference, six half-day workshops were organized that presented major themes of the conference. Here, we focus on the outcomes of the Robotics workshop[9]. The workshop brought together renowned scientists to discuss the 10 years of progress and future challenges in the fields of active touch and vision perception, grasping and manipulation, neuromorphic vision systems, human–robot interaction, brain–computer interfaces, and cognitive architectures. In this perspective paper, we present the 10 years of progress and future challenges of some of the key themes of the field presented in the workshop. More specifically, the creation of artificial systems that can robustly interact with their environment, ranging from tactile sensing, grasping, and manipulation to the creation of psychologically plausible agents.

2. Robotic tactile sensing

Biomimetic tactile sensing is needed for the development of autonomous robots capable of interacting with the surrounding environment and reaching human-like dexterity. These are easy tasks performed by humans but they represent highly complex processes for robots. Particularly, due to the challenge in artificial tactile sensors to mimic the data formats that can be captured by the human skin. For these reasons, a variety of devices has been developed in the last decade using different approaches including sensing technologies, soft materials, sensor morphology and data processing methods trying mimic receptors and functionalities of human hands and fingers. Examples of advanced tactile devices include the TacTip, Gelsight, BioTac, iCub skin, HEX-o-SKIN, and GelTip which use single and combination of sensing elements.

Soft biomimetic tactile sensors are sensing devices based on principles distilled from the study of biological touch [3, 4]. True biomimicry approaches seek to the transduction principles of human skin into the design of an artificial sensor. Soft robots are often inspired by soft-bodied animals [5], therefore, biomimetic tactile sensors are usually soft. There are, however, many ways in which biological principles can motivate soft designs. In recent years, the combination of soft materials with optical and biological principles underlying the sensor of touch has motivated the development of advanced biomimetic tactile sensors. A clear example is the TacTip sensor [6], which is described in the following sections.

2.1. Biomimicry of human touch with the TacTip sensor

Recently, a close similarity has been found between the neural responses from human touch and those from the biomimetic TacTip skin [7]. Slow and rapid adapting (SA and RA) mechanoreceptors underlie our sense of touch. By modeling the activity of these mechanoreceptors in the biomimetic skin, the study found that the artificial tactile signals match those measured from tactile nerves in the original pioneering studies of human touch from 40 years ago. This was the first time that such a close match between artificial and natural tactile skin had been found.

A companion study [8] focused on the complementary aspect that human skin has a vibrational (RA-II) sense alongside the slow and rapid adapting (SA-I and RA-I) components of our skin. This vibrational sense was built into the TacTip by using tiny microphones embedded in the skin. This biomimetic tactile skin was tested for its capability to feel the roughness of different textures. Both the artificial vibrational sense and the RA mechanoreceptors could feel texture well, but the SA mechanoreceptors cannot. As this is also known to be the case for human touch, the combined biomimetic tactile skin acts more like human skin in combining spatial, temporal, and vibration-sensing modalities.

2.2. The TacTip design

The TacTip design has evolved over a decade to diversify into a family of tactile sensors, tactile hands, and tactile robotic systems [6,17]. Two fundamentals underlie its design and function-compliant materials and optical image sensors. First, the deformation of a soft sensing surface is transduced into a movement of markers attached to pins on the inside of that surface. Second, the movement of markers is captured by an internally-mounted camera. The fabrication process of the sensor surface is a key aspect of this sensor going from a single-material printed sensor body [15] to multi-material printing approach [17]. Multi-material 3D printing was crucial in easing the sensor fabrication, which led to a rapid cycle of development, testing, and refinement when combined with a simple, modular design (figure 1).

2.2.1. *Sensor outer skin (epidermis)*

The original TacTip in 2009 [15] had a molded skin with nodular pins on its underside, cast as one piece from urethane rubber; the pin tips were (painstakingly) painted white by hand, and the skin attached to the sensor body by a cable tie. Later versions

[9] Living Machines conference https://livingmachinesconference.eu/2021/conference/.

Figure 1. Development of the TacTip biomimetic tactile sensor. Left: relation to other types of tactile sensor; the TacTip uniquely combines features of biomimetic [9, 10], soft [11, 12] and optical [13, 14] tactile sensors. © 2021 IEEE. Reprinted, with permission, from [6]. Right: timeline for development from the original TacTip [15], to the 3D-printed version [16], miniaturization for a robotic gripper [17], further miniaturization for anthropomorphic robot hands [18], open-sourced 3D-printed version [6] and open-sourced integration into a common base for GelSight/DIGIT and TacTip/DigiTac optical tactile sensors [19]. Reproduced from [17]. CC BY 4.0. © 2021 IEEE. Reprinted, with permission, from [18]. © 2022 IEEE. Reprinted, with permission, from [19].

included a skin made from multi-material 3D printing: the sensing surface and inner pins were printed in a black rubber-like material with attached pin tips and mounted in hard white plastic. Numerous versions of the outer skin have been developed for the TacTip including pin layouts, shapes/sizes, skin structures, and other modifications [6].

2.2.2. Sensor inner gel (dermis/subcutis)

The sensor skin is filled with a soft, optically-clear silicone gel that gives the sensor tip elasticity, compliance and allows the markers to be imaged. This elastomer gel is held in place by a transparent rigid acrylic seal on the underside of the tip. The hardness of the elastomer varies and is analogous to the stiffness contrast between the harder epidermis and the softer dermis of human skin. This contrast underlies the transduction of skin deformation into pin movement: the outer surface bends to reorient the markers on the pin tips, and rapidly reforms when unloaded. Additionally, the inner gel protects the internal electronic components of the sensor from damage, mimicking the protective function of the human subcutis.

2.2.3. Sensor camera and mount

The tip of the sensor, comprising the outer skin, elastomer gel, and sealing cap, is mounted on a 3D-printed body that houses the camera and other electronics and the camera used depends on the application. Earlier versions utilized webcams like the Microsoft Lifecam. Although such approaches eased construction, they resulted in bulkier devices (161 mm) [20], whereas more compact designs have been assembled ever since (85 mm) in newer models. The camera choices ranged from disassembled LifeCams [17] to high-performance, off-the-shelf ELP camera modules [21]. Multiple designs have been explored for the TacTip to balance constraints on camera/lens size, performance, connectivity, cost, weight, and hardware availability [6].

The TacTip sensor has been integrated into a variety of robotic hands, which required innovation in the use of a camera. For hands with large fingertips, such as the Model-M2 [22], Model-GR2 [23] and Shadow Modular Grasper [24], it was sufficient to use a camera circuit board with wide-angle/short-focal-length or fisheye lens. For tactile signals from multiple fingertips, plug-and-play USB cameras are easier to use. Current solutions include the ELP module (standard TacTip), the JeVois camera for the 3-fingered Model-O hand [25], and the Misumi Model SYD USB camera integrated into the fingertips of an anthropomorphic Pisa/IIT SoftHand [18].

2.2.4. Modularity

A useful design feature of the redesigned TacTip (2016) is to have a modular assembly so that individual components can be adapted or re-used [17]. The skin is printed in a single structure attached to a hard plastic casing, forming a tip that connects to the TacTip base with a bayonet mount. The tip (comprising the skin, gel, sealing cap, and plastic casing) is thus a modular component of the sensor that is easily replaced, interchanged, or upgraded. Additionally, the tips can be either 3D-printed or molded, and can be fabricated in a variety of sizes, textures, or pin layouts. As a design, it can be an ideal platform for tactile sensing investigation, we it can be attached to industrial robots or integrated within robot hands. Overall, the construction of the TacTip is easy to assemble, requires some know-how and soldering skills, but its modular design allows for customizable and multi-material designs (3D printing) and a wide range of materials for cheap and quick bulk fabrication (molded skin).

3. Robotic grasping and manipulation

Robotic grasping has been studied extensively in the literature as a manipulation primitive that immobilizes an object with respect to a robotic hand [27–33]. In the general process for grasping an object, a robot hand positions its finger/palm links such that they contact and apply forces at a particular set of points on a given object. These contacts create a set of constraints on the motion of the object that can be analyzed to deduce whether the object is immobilized, e.g. through form or force closure [34, 35]. This field has seen an exponential growth of attention with the progress made in areas of perception, planning, and control crucial for grasping and manipulation tasks. The interest from the general public, industries, and government agencies has contributed to developing new applications and case scenarios from simple pick-and-place to handling packages or assembly of mechanical components. Nevertheless, the field has not grown evenly; some challenges received or are still receiving a great deal of attention, while others remain unsolved and unpopular. The evolution of the robotic grasping and manipulation field can be seen in figure 2.

3.1. Robot mechanical design and software

Reliable grasping and manipulation in real-world applications are still out of reach due to several reasons. (a) At a mechatronic level, simple end-effectors, such as parallel grippers eliminate model complexity and redundancy at the cost of strong limitations for object grasping and manipulation. Anthropomorphic end-effectors provide essential features for manipulation, such as movable thumbs or rolling fingers, but the control complexity and lack of adequate sensing make these devices impractical. (b) At an algorithmic level, the robotic manipulation pipeline requires modules whose robustness and resilience are challenged by even minimal changes in the setup or environmental conditions. Furthermore, robots need to be capable of understanding the state of the surrounding environment, however, encoding any conceivable condition that a robot may face is not a viable solution. Research suggests that biological brains could work as Bayesian machines [36, 37], offering generative models, whose priors are combinations of model-based and data-driven experience.

3.2. Generative models, perception and grasping strategies

Generative models (GMs) such as kernel density estimation (KDE) or deep learning (DL) are well-established robotics tools. GMs attempt to learn the true distribution of data from sampled observations. When faced with previously unseen data, they rely on learned features to find common patterns and compute valid candidate solutions. Training GMs for robotics is challenging due to the need for physical interaction data, which is hard to generate from real and unstructured environments.

A significant amount of work has been dedicated to robot perception to deal with unstructured environments using depth cameras and high-precision tactile sensors [40, 41]. Nevertheless, the robot perception process can be affected by sensor limitations such as occlusions, shiny or translucent materials, and noisy tactile data. Rather than attempting to eliminate the source of uncertainty, robots need to learn how to deal with it. In [38], a deep learning framework used in a simulated robot drummer collects audio, video, and proprioception data to retrieve the missing information from the other inputs when a modality is faulty (figure 3(a)). Robots should use perception uncertainty as an indicator to modify their behavior, where high uncertainty should lead to more conservative strategies. For example, reaching into the fridge to grasp a bottle that they can only partially see and how this would affect their reaching strategy. Robots can achieve this by integrating perception uncertainty from their sensors into their motion planner [39,42–45] (figure 3(b)). Perception uncertainty has been explored with the humanoids Vito (Centro Piaggio at the University of Pisa) and Boris (Intelligent Robotic Lab at the University of Birmingham) (European FP7 grant PaCMan [46]). In [47], the robots outsmart in-hand self-occlusions and vision-driven uncertainty by combining visual clues and clever tactile exploration of the object's surface.

Over the last decade, one of the breakthroughs in grasping and manipulation was to shift from a grasping-centered approach to a contact-centered approach formulations [48]. This change had implications in terms of the world models, planners, controllers, and sensing and perception methods. A comprehensive review of this specific field can be found in [49].

3.3. Grasping-centered approach to robotic grasping and manipulation

The grasping-centered approach offers multiple advantages to develop robotic manipulation systems. First, immobilizing the object to be grasped simplifies the problem of motion generation for the manipulator, allowing it to be cast as a collision-free path planning problem, solvable using e.g. rapidly-exploring random trees [50] or probabilistic roadmaps [51]. This simplifies the problem of modeling the world since only a geometric/volumetric model is necessary to check for collision. This approach simplifies the estimation of the world state, required only at the beginning of robot motion through a vision/depth sensor [26, 52], enabling the sense-plan-act paradigm and

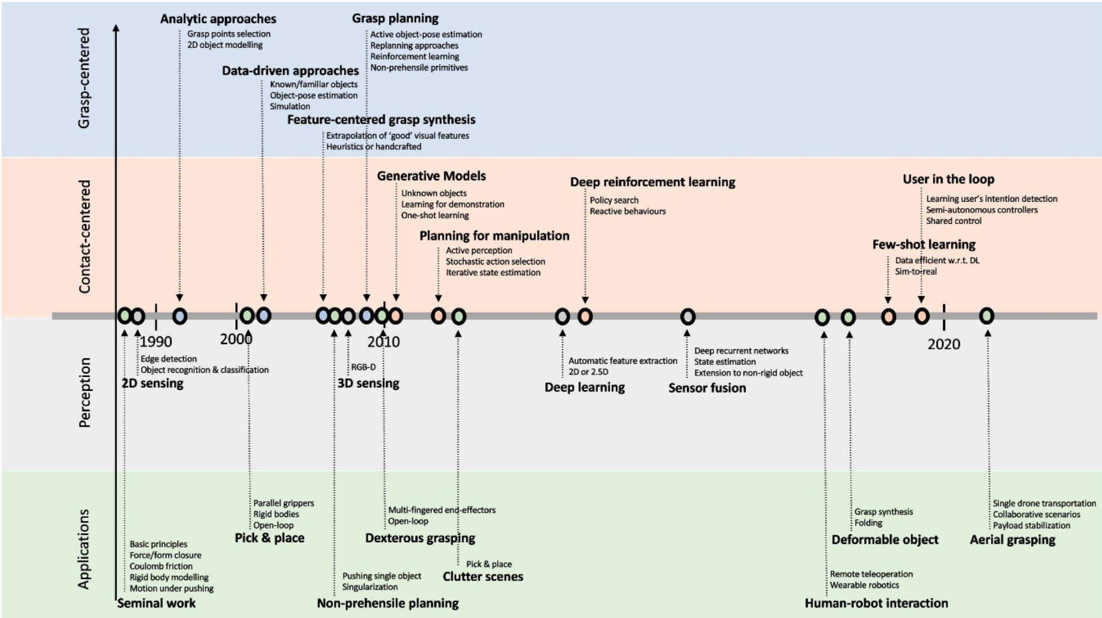

Figure 2. The figure shows the evolution of the robotic grasping and manipulation field. The research before early 2000 should be considered seminal work and primarily achieved with analytic approaches on a grasp-centered perspective. In 2008, the work in Saxena *et al* [26] spawned the idea of looking for visual features for synthesizing grasp poses. The availability of depth sensors in 2009 introduced new 3D features. In early 2010, the paradigm switched to contact-centered grasping, which still dominates the field. Deep learning has revolutionized our perception capabilities and action-selection learning but at the cost of being data-inefficient. The late trend is to investigate more data-efficient methods such as one- or few-shot learning. Very recently, autonomous grasping and decision-making has been merged with HRI to combine users' cognitive abilities with reliable automation. In 2022, aerial transportation and payload stabilization have become extremely popular, catching the grasping community's attention.

(a) (b)

Figure 3. (a) Top: simulation setup for drumming task in Gazebo. The colored surfaces represent target regions that generate audio. Bottom: schematic of our framework. Input is given as a drum tab, or desired beats for each element of the drumkit. Reproduced from [38]. CC0. (b) Justin robot in starting configuration, the mug to be grasped (glued on the desk), and the depth camera (left). Justin executes a successful reach-to-grasp trajectory which leads to grasping the mug (right). © 2013 IEEE. Reprinted, with permission, from [39].

'open-loop' manipulation. Consequently, leading robotic manipulation systems [53–57], and software [58, 59] focused on this grasping-centered pick-and-place manipulation approach. The grasping-centered approach has also significant limitations. First, it restricts robotic manipulation to pick-and-place operations, whereas humans manipulate objects in a variety of ways, e.g. pushing, toppling, bending, or folding. Second, this approach fails in uncertain and cluttered environments, where collision-free motion is difficult to achieve. Third, static volumetric representations of the world limit the interaction to mainly rigid objects. Fourth, this approach makes it difficult to integrate continuous contact-sensing information into the planning and control processes.

3.4. Contact-centered approach to robotic manipulation

The contact-centered approach overcomes the limitations of the grasping-centered approach by viewing

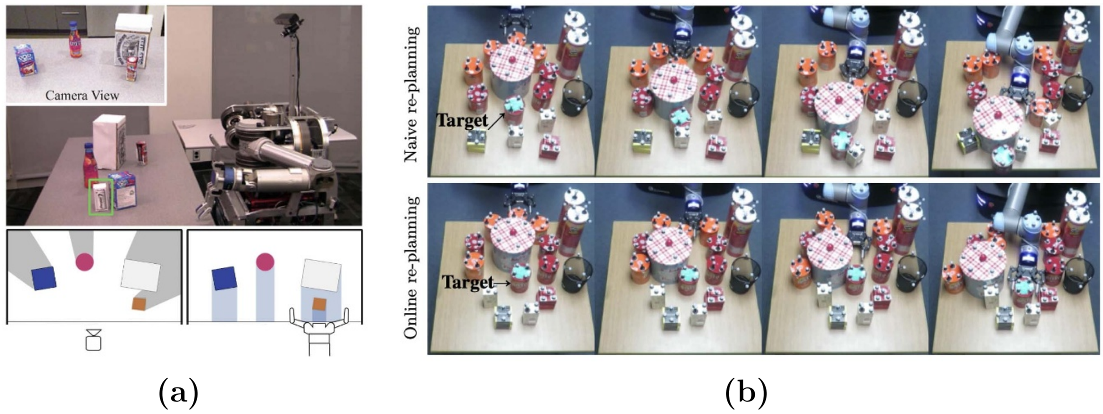

Figure 4. (a) Object search by manipulation. The robot is searching for a target object (highlighted by the bounding box) on the table, but its view is occluded (drawn as gray regions) by other objects. The robot must remove these objects to search for the target. Objects may block the robot's access to other objects. Reproduced from [60], with permission from Springer Nature. (b) Real-time online re-planning for grasping under clutter and uncertainty. Top row: Naive re-planning (no added uncertainty) fails to grasp the target. Bottom row: Online re-planning succeeds. © 2018 IEEE. Reprinted, with permission, from [61].

grasping and manipulation as a sequence of contact interactions. This approach builds on the non-prehensile manipulation method [62] with early works on quasi-static pushing and dynamic interactions with objects [63–66]. The contact-centered approach includes grasping actions and views them as contact-interactions with the object, while non-prehensile manipulation excludes grasping.

Starting in the 2010s, the contact-based manipulation operations gained a wider interest for trajectory optimization and optimal control methods such as the iterative linear quadratic regulators and differential dynamic programming [67], and direct transcription-based methods [68, 69]. There were also efforts to extend existing motion planners with non-prehensile primitives and pushing primitives [70–73]. Such approaches made possible what is called 'manipulation in clutter', where a robot interacts with a pile of objects simultaneously to retrieve a particular object [74–79] or to search for an object obstructed from view [60] (figure 4(a)). The Amazon Picking Challenge in 2015 [80] raised interest in robotic manipulation in warehouses, where robots needed to perform manipulation inside cluttered multi-object shelves and packages. This further raised the interest of manipulation in clutter (figure 4(b)) [81–89,104]. The deep-learning revolution also affected robotic manipulation. The reactive policies that can be learned through reinforcement learning are a good match to contact-based manipulation. While the collision-free motion of the grasp-centered approach did not require a reactive framework, the stochasticity of contact interactions [90] made it difficult to follow a pre-planned control sequence. This motivated the training of deep-reinforcement-learning policies for contact-based manipulation [91–94]. The contact-centered approach still has challenges and opportunities including the following ones.

3.4.1. World models including contact interactions

This approach requires modeling contact interactions which can use simplified quasi-static pushing models [95], or general dynamic simulations such as offered by Mujoco [96], PyBullet [97], or DART [98]. The computational expense of these simulations is challenging, and motivated recent work on coarse physics predictions during manipulation planning [99]. Toussaint *et al* [100] use different abstractions of physics for manipulation planning with tool use. There is a recent interest to learn such dynamics models [101, 102] instead of running computationally expensive simulations during planning.

3.4.2. Reactive planning and control

Contact interactions are difficult to predict, and therefore a generated motion plan can quickly become invalid under unexpected object motion. This differs from the grasp-centered approach, where the object either does not move or moves rigidly attached to the robot hand. Therefore, while the grasping-centered approach requires only one planning cycle, the contact-centered approach requires updating often, usually achieved using model-predictive-control approaches [61, 67, 69], or reactive policies with reinforcement-learning-based methods.

3.4.3. Continuous estimation of objects' state

Reactive execution requires the continuous estimation of the environment's state. As opposed to the grasping-based approach, which requires a single estimation of the object poses from an initial visual snapshot, contact-based manipulation requires tracking the object poses over time [103, 105].

3.4.4. Use of contact sensors

Contact-based manipulation offers more opportunities to use tactile sensing during manipulation

[103, 106, 107]. Existing tactile sensors usually cover a small area on the robot end-effector (e.g. the fingertip), which makes it difficult to rely on them for continuous information during manipulation.

3.4.5. Extensions to non-rigid objects

The approach of modeling object and contact dynamics supports extensions to deformable object manipulation, which has seen growing interest [108–111]. A challenge is the computational expense of the simulation and state perception of deformable objects.

3.5. Geometrical features and learning from demonstration

Geometrical features from the physical object contacts can be obtained with the contact-centered approach, and are typically extrapolated around the contact points in a paradigm called learning from demonstration. Here, a teacher presents a feasible and robust contact to the robot; from the geometrical features, enough statistic is acquired to learn contact densities in a one-shot fashion as generative contact models [112, 113]. Since many objects share many local geometrical features, these models tend to generalize very well within and across object categories. Task-dependent constraints can be added in the formulation as optimization procedures, but this requires a good knowledge of the task and ad-hoc solutions. Very recently, a contact-based formulation has also been successfully applied for the first time to the problem of aerial grasping [114]. Although it should be considered a seminal work, the proposed framework extends the one-shot learning paradigm enabling unmanned aerial vehicles with cable-suspended passive grippers to compute the attach points on novel payloads for aerial transportation with no need for handcrafted task-dependent features.

3.6. Internal models for prediction while interacting with objects

Contact-based approach and generative models have been investigated with internal models to predict the outcome of the interaction with an object in both known and novel contexts. This approach is inspired by the way that humans learn internal models of the world from data-driven experience and curiosity-driven interaction. In [115, 116], the contact-based formulation enabled the learning of an internal model for predicting push motions of previously unseen objects, while in [117] a planner uses black-box motion predictors to move objects to the desired configurations. Although the theory behind motion prediction is well-established, the existing methods are not yet used in industrial applications, as no robot can insert a box onto an over-the-head store shelf by exploiting push operations and the relative contacts and forces generated [118].

3.7. Grasping and manipulation in physical human–robot interaction

Another field that has shown growing interest is that of physical human–robot interaction (pHRI) [119], where a human operates with a robot to accomplish manipulative tasks. Remote pHRI is crucial to guarantee the safety of a human operator in dangerous tasks [120–122]. Intuitive and accessible interfaces are required in pHRI to allow the robot to reliably interact with the human and estimate their intention from biological and behavioral clues and map this into appropriate robot motion commands [123]. For example, an AI assistant for teleoperation responds to the user's motion intentions in a predict-then-blend fashion by perceiving a cluttered scene, predicting candidate grasps for the visible objects, and, for each grasp, computing a feasible motion plan [124, 125].

4. Biomimetics in the body and mind of social robots

Social robotics and human–robot interaction (HRI) are two other emerging fields that have gained increased interest over the past years. The evolution of the field of HRI is presented in figure 5. The impact of social robotics is two-fold. On the one hand, it can embody human-like reasoning and mimicking of human behaviors and movements in a robot, resulting in the creation of an agent that satisfies human expectations and therefore, can socially resonate with humans. On the other hand, such agents can be used as a testbed for testing theories to better understand human social cognition using a systematic approach [126]. Thus, both the robot's morphology and behavior play a crucial role in perceived interactions and the creation of Living Machines.

The robot's morphology can be used to leverage the knowledge of human communicative behavior [139] and is critical for establishing successful communication [140]. The versatility of possible design strategies employed in HRI scenarios can bias the interaction and may affect the user's perception and expectations about its social capabilities. The general disposition is to design robots that allow humans to anthropomorphize them since anthropomorphism occurs naturally in humans [141], and their appearance highly depends on the task they are required to perform. For example, zoomorphic social robots, like the robotic seal Paro can be beneficial to the mental healthcare of the elderly [142], while humanoid robots with cartoon-like features such as the Zeno robot or the Nao have been extensively used in Child-Robot Interactions (CRI) [143, 144]. These robots have limited expressiveness compared to more sophisticated humanoid robots, raising fewer expectations about their cognitive capabilities, and so inverting the negative reaction described by the Uncanny Valley hypothesis [127].

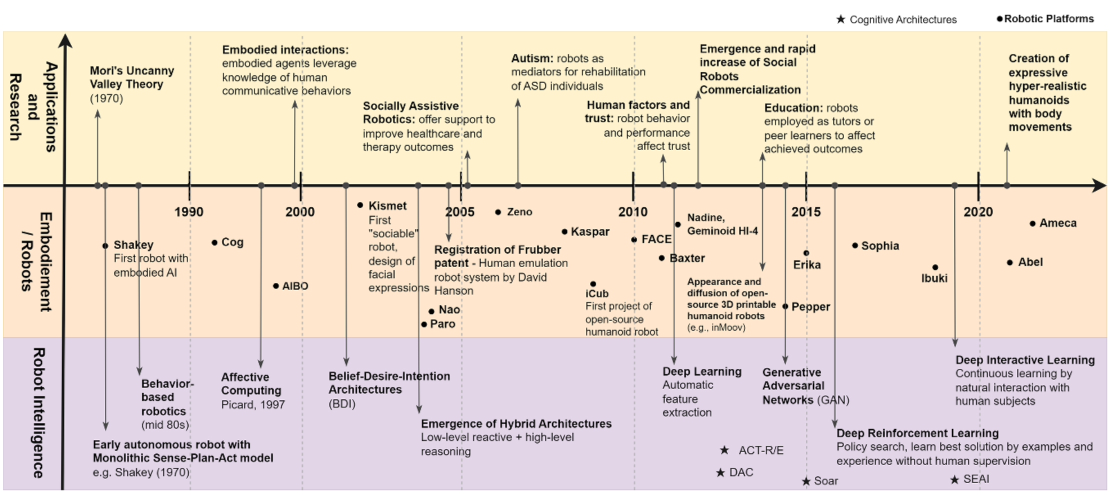

Figure 5. The figure shows a short summary of the evolution of the field of human–robot interaction over the years. The work presented before 2000 can be considered as seminal work that paved the road for the development of the field of social robotics. For example, the Uncanny Valley [127] is still often used to explain the potential rejection of anthropomorphic robots. Additionally, early enough, Affective computing as a field [128] highlighted the importance of the study, design, and development of emotional systems, while embodied interactions are crucial for social cognition [126]. From that point on, a plethora of research fields emerged, ranging from Socially Assistive robotics [129], where robots offer support to improve healthcare and therapy outcomes, including Autism [130], to educational robots [131], while the effects of human, robot and environmental factors that affect HRI and trust became crucial in the field [132]. In parallel to these research fields and with the advancement of technology, a variety of robotic platforms were developed not only as research platforms but also to serve the purpose and application for which they were designed. Early examples include Kismet (the first sociable robot with facial expressions), and other anthropomorphic robots such as the Nao, the iCub, and zoomorphic ones like the Paro. As time passes, we observe also the development of hyper-realistic humanoids such as Sophia, Ameca, or Abel. Finally, the generation of believable and social behavior was highly influenced by the implementation of machine learning algorithms as well as cognitive architectures such as ACT-R/E [133], Soar [134], SEAI [135] or DAC [136] on artificial agents that interacted with humans.

(a) (b)

Figure 6. (a) A detail of Abel's head. On the left the head is covered with bioinspired skin-like material; on the right the internal mechatronics exposed, designed to perform facial expressions, gaze behavior, and lip-sync speaking. Reproduced from [137]. CC BY 4.0. (b) Experimental setup to understand human trust in machine partners: a humanoid robot with high human-likeness (FACE), a human counter-part (Human), and a computer-box machine (Computer-Box). Reproduced from [138]. CC BY 4.0.

Nonetheless, the capability to express human-like emotions is particularly important in education, in interactions with individuals with neurodevelopmental disorders, e.g. autism spectrum disorder [145, 146] and attention deficit hyperactivity disorder [147], as well as individuals suffering from neurodegenerative diseases or presenting milder symptoms of dementia [148, 149]. The development of social robots that closely resemble humans has demonstrated to be effective in various HRI scenarios [150], and their similarity to humans becomes crucial if we consider their role in the activation of motor resonance, which is directly linked with social resonance and empathy [151]. Therefore, we can expect an increased interest in the design and development of highly realistic humanoid social robots, such as Abel, which is currently under development [137] (figure 6(a)).

Part of the research interests in HRI scenarios is the investigation of decision-making [152], perceived interactions [153, 156] and the development of trust [138, 154] (figure 6(b)). These examples identify anthropomorphism (or 'humanness') as a key component that improved acceptance and trust. This highlights the need for further studies of the effects of human likeness that go beyond the simplification of the Uncanny Valley hypothesis [155] by evaluating long-term interactions in real-world scenarios with a deeper analysis of human emotional reactions. The real-time extraction and analysis of the user's physiological parameters can give insights into the internal state of the human and allow the robot to adjust its behaviors accordingly. To do so, researchers typically employ wearable or contactless sensors for the acquisition of biosignals such as electrodermal activity, electroencephalography, the analysis of thermal images, and state-of-the-art audiovisual systems. Many works already confirmed the effectiveness of analyzing these responses to optimize the behavior of social robots [157–161]. Consequently, a desirable evolution for social robots is the integration of such sensors, to augment both the robot's body and 'mind'. By extending the robot's cognitive and decision-making system with the real-time extraction and analysis of these physiological parameters, we can achieve a more reliable assessment of human emotions. This, in turn, will lead to a better adaptation of the robot to the social context in which it is immersed.

Nonetheless, a hyper-realistic morphology with advanced expressive possibilities, and enhanced with multi-modal perception, does not suffice for robots to be considered social agents. For a robot to be accepted as a social partner, it needs to be autonomous, make decisions, and perform actions without human intervention, and therefore, their cognitive system plays an essential role. What emerges from the recent literature regarding control architectures for social robots, is the confirmation of a subdivision between two suitable approaches. The data-driven approach of machine learning algorithms (e.g. deep learning, deep reinforcement learning) has proved to be fundamental for the training of cognitive modules dedicated to attention [162], the extraction of social cues from the environment [163], the classification of the extracted information [164, 165], as well as imitation and learning [166]. This approach is typically used for the emulation of quick or unconscious human behaviors and capabilities, but neural networks can also be useful to enhance artificial social agents with creativity and imagination, as in the case of generative adversarial networks, already used to create images and videos starting from a known dataset [167]. A symbolic approach is instead preferred for high-level reasoning, decision-making, behavior generation, and the modeling of emotions influence decisions [168–170]. This approach is more suitable to encompass mechanisms that allow for the generation of plausible social behaviors, whose biological basis might be too complex or unknown but can be easily described semantically, like emotional states, beliefs, or goals. An example is the distributed adaptive control (DAC) biologically grounded cognitive architecture that has been integrated into social robots for the generation of psychologically valid behaviors on a variety of different interaction scenarios [136, 171, 172], and the Social Emotional Artificial Intelligence (SEAI), an hybrid cognitive system inspired by neuroscience theories on human emotional processes and decision-making, specifically conceived for social and emotional robots [135]. Such integrated architectures and approaches (i.e. encompassing all sensorimotor aspects as well as cognitive processes) are necessary for generating plausible reactions and adaptive behaviors of robots in complex, dynamic, and uncontrolled social contexts, to be able to create socially competent Living Machines.

5. Living machines: a sneak peek of the future

We are living in undoubtedly exciting times, where research in biomimetic systems and a plethora of interdisciplinary fields are advancing rapidly. For this reason, the Living Machines conference seeks to provide an environment that promotes the presentation, evaluation, and discussion of cutting-edge and next-generation technologies. To celebrate its 10th anniversary, we organized a series of workshops, and in this perspectives paper, we present the 10 years of progress, challenges, and future of artificial systems that can robustly interact with their environment. Examples include the presented novel approach for robotic tactile sensing based on the human hand to acquire rich contact information, a plethora of progress and current approaches for robotic grasping and manipulation, as well as current advancements in the creation of social synthetic agents.

The next decade will be even more exciting for the field of robotic tactile sensing, grasping, and manipulation. Although there are fundamental problems to be addressed in intelligent robotic interaction with complex environments, once solved, they will open up many application areas across engineering and robotics. In the case of tactile sensing, one key problem is that there is a huge gap between what is achievable in research laboratories and what is known about human dexterity and our sense of touch. This will require progress toward two interconnected goals: (a) to advance knowledge of how our sense of touch leads to haptic intelligence by embodying those capabilities in robots; and (b) to improve the intelligent dexterity of robots with accessible robot hardware and software. Reaching human-like levels of dexterity has been the vision for industrial robotics for years and the use of biomimetic touch to achieve that goal has driven developments in robotic tactile sensing since the 1970s. A combination of advances in soft robotics, biomimetic tactile sensing, and AI could enable that vision to become reality.

For robotic grasping and manipulation, we observe a tendency toward more flexible and reliable approaches [173] as opposed to highly-engineered solutions. At the current state, grasping with imperfect perception is still one of the main issues that slow progress and it will require both research and engineering work [174]. In-hand manipulation is still at its dawn. Clever designs of tools and end-effectors can achieve specific in-hand manipulation, but without adequate sensory feedback and clever control strategies, this problem remains one of the most challenging tasks a robot can face. Hardware and software integration is still tedious and time-consuming, but multiple efforts have been made to alleviate it with tools such as the Robot Operating System [175], Yet Another Robot Platform [176] that facilitate communication, synchronization, and modularity between software and hardware. At this pace, it is safe to assume that robust and precise grasping will be consolidated for many different scenarios and applications with advanced robot pick-and-place in the agricultural industry and delivery services. Beyond pick-and-place tasks, many of the current solutions will fall apart. Grasping for manipulation purposes needs planning while considering task-dependent constrains. Many of these constrains are hard to encode and on-the-fly generation of contacts yields unreliable solutions even for known objects. This will remain a hard challenge for the next decade on which many researchers will focus their attention. Finally, in the last decade, we have observed an increasing interest in pHRI with exoskeletons and prosthetic devices getting smarter and a large amount of effort has been and will be, dedicated to investigating more intuitive interfaces for manipulation as well as augmented and virtual reality technology.

Finally, the future perspective for social robots will focus on the development of advanced cognitive systems combined with perceptive capabilities that will increase the amount and reliability of the information obtained from their social environment. Particular emphasis will be given to the social robots' personality and behavior design, representation of emotions and their influence on the robot's decision-making, and applications in real-world settings. Such approaches will enhance the psychological believability of expressive social robots, bringing them one step closer to the creation of Living Machines.

Data availability statement

No new data were created or analysed in this study.

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